





### Computational Mathematics

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### **2013 AFOSR SPRING REVIEW**



**NAME: Fariba Fahroo** 

#### **BRIEF DESCRIPTION OF PORTFOLIO:**

**Discover Mathematical Algorithms** and Develop Computational Techniques that Provide More **Accurate**, **Reliable**, and **Efficient** Algorithms for Modeling and Simulation and Design of Complex Systems for the U.S. Air Force with radical cost and turn-time improvements.

### **LIST SUB-AREAS IN PORTFOLIO:**

Multi-Scale Modeling (materials, plasma, structures, fluids, combustion)

Multi-Physics Modeling (fluid-structure interactions, particle-fluid models)

Uncertainty Quantification

Multidisciplinary Optimization and Control (Design Under

Uncertainty)

New Emphasis on Scalable Algorithms in All These Sub-Areas



## Comp Math Transformational Opportunities for the AF



**Goal:** Simulation, Analysis and Design of complex systems with radical cost and turn-time improvements

Needs for Computational Math: Support for Accurate, Reliable, and Efficient novel, mathematically sound, and verified algorithms for complex AF applications such as in plasma, structures, combustion, fluids, and so on.

### AF Examples: 1) Simulations of High Power Microwaves (Dr. Luginsland)

- Need for 3D, high-fidelity, parallel modeling of high energy density fields and particles in complex geometry --- AFOSR comp math support
- 2) "Digital Twin" (Dr. Stargel): Real Time, High-Fidelity Operational Decisions for Individual Aircraft Enabled by Tail Number Health Awareness: Need for Material Scale modeling, Deterministic Multiscale Modeling, Uncertainty quantification Key research areas in comp math supported for several years.
- 3) Turbulence Combustion (Dr. Li): Need for new numerical and mathematical approaches for multiscale, multiphysics modeling Key research area in comp math
- 4) Aerospace Materials for Extreme Environments (Dr. Sayir): Need for theoretical and computational tools that aid in the discovery of new materials and Mathematics to quantify the microstructure --- A new research thrust





## Transformational Opportunities for Computational Math



### Predictive High-Fidelity Simulations for AF Applications

- More computing power based on emerging heterogeneous computing architecture BUT computing power isn't everything
- Challenges: Issues with system Power, Slower growth in Memory bandwidth, Cost
  of data movement, Slower growth in clock rate and move to Concurrency of higher
  number of nodes and threads, Slower growth in I/O bandwidth, Resiliency and Reliability
  of the computing systems

### We Need Fundamental Paradigm Shifts in Algorithms, Software, Architecture Design

- 2 Basic Research Initiatives in 2012 → Ultra-scale Algorithms(with Dr. Luginsland), and Co-Design (with Drs. Luginsland, Smith, Stargel)
- For Co-Design, the emphasis was on integration of research threads into a coherent agenda for specialized, high-performance computing architectures for Air Force and DoD applications.
- For Ultra-Scale Algorithms the focus was on mathematical aspects of scalable solvers with emphasis on parallelism across scales (spatial and temporal), high-order discretization, and multi-level domain decomposition techniques.





## Portfolio's Focus Areas and Outline of Research Highlights



- High-Order Methods of Accuracy(the sole funding agency to support these methods across various application areas such CFD, Structures, Plasma, Combustion):
  - An interplay of Efficiency ,Accuracy and Robustness---- Serious need for mathematical development of these methods for capturing complex multiscale physics in an accurate AND efficient way
    - Highlight of a CFD effort
    - Highlight of a Combustion effort
- Multiscale Methods: Materials need for more mathematical and computational techniques for bridging the scales
- Uncertainty Quantification: Need for more mathematics in modeling and analysis of stochastic phenomena
  - Design Under Uncertainty -- a 2012 BRI topic
  - Bayesian Framework for UQ → a MURI 2012 in Material Science
  - Scalable Algorithms for Inverse Problems



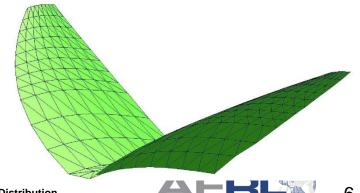


### A High-Order IMEX Scheme for FSI

Persson (UC Berkeley)



- Many important problems require predictions of fluid-structure interaction (FSI):
  - Oscillatory interactions in engineering systems (e.g. aircraft, turbines, and bridges) can lead to failure
  - The blood flow in arteries and artificial heart valves is highly dependent on structural interactions
- Two main numerical approaches for the coupling:
  - Fully coupled (monolithic): Solve the fluid/structure equations simultaneously. Accurate, but requires specialized codes and solvers are often slow.
  - Weakly coupled (partitioned): Use standard solvers for fluid/structure and apply a separate coupling scheme, often together with sub-iterations. Efficient and simple, but issues with accuracy and stability.
- Approach: Use Implicit-Explicit (IMEX) schemes to obtain high-order accuracy without coupled solvers or iterations
- **Using high-order spatial DG and FEM schemes** for the fluid and the structure, up to 5th order of temporal accuracy with the IMEX scheme is obtained

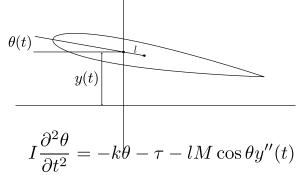


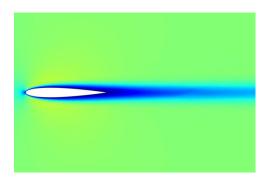


### **Benchmark Airfoil System**

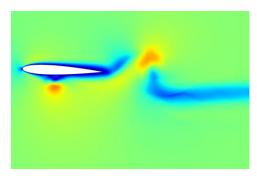


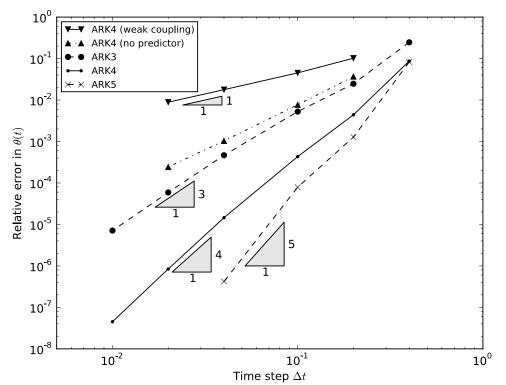
- High-order DG for Navier-Stokes, ALE for moving domain
- Rigid pitching/heaving NACA 0012 airfoil, torsional spring
- Up to 5<sup>th</sup> order of convergence in time
- Without the predictor, at most 2<sup>nd</sup> order of convergence





$$t = 0.0$$



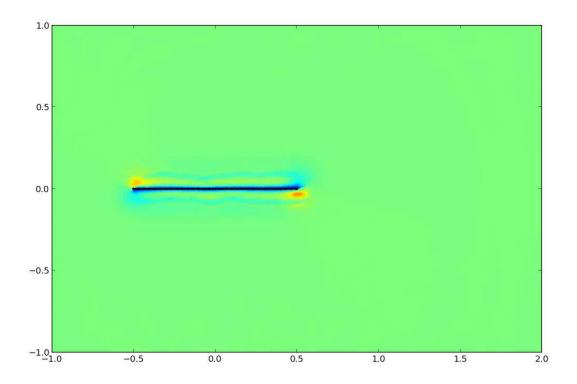




### Fluid/Membrane Interaction



- Hyper-elastic neo-Hookean membrane with viscous, fluid-like, dissipation
- Membrane ends are held fixed but allowed to rotate
- Fluid has 20 degree angle of attack and Reynolds number 2,000
- Implicit schemes easily handle complex behavior with large time-steps







### Flame Roll Up in a Vortex: Overview

Mitchell D. Smooke --- Yale University



- Optimal numerical methods for chemically reacting flows will ultimately have to be both locally adaptive and high order
- Diffusion Flame-Vortex Interaction
  - Canonical configuration facilitating a first-principles understanding of aspects of turbulent combustion (e.g., flame stretch, local extinction, soot production)



Hsu, et al., *Phys. Fluids A* (1993)

### Simplified Flame-Vortex Models

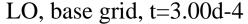
- Convection-diffusion-reaction equations with imposed flow field
- One-step or multi-step finite-rate Arrhenius chemistry
- Variable mechanical timescale related to a vortex Reynolds number
- Benefits of simplified models:
  - Faster development of tailored numerical methods for complex problems
  - Imposing the flow facilitates joint theoretical and computational work

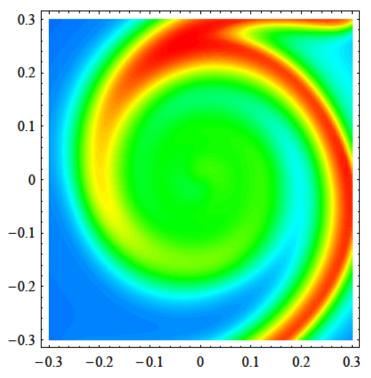


### Flame Roll Up in a Vortex – Re = 600

### **Conventional method under grid refinement**







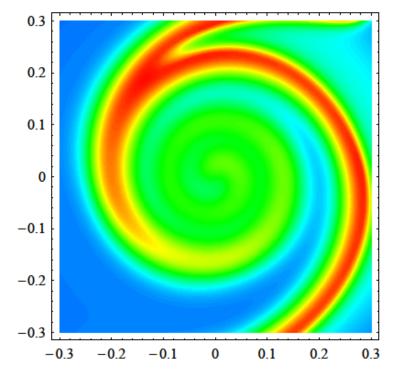
### Spatial discretization

• Grid: quasi-uniform,  $\Delta x \approx 0.008$ 

Order: 1<sup>st</sup> (upwind scheme)

CPU factor: 1

LO, refined grid, t=3.00d-4



### **Spatial discretization**

• Grid: quasi-uniform,  $\Delta x \approx 0.004$ 

Order: 1<sup>st</sup> (upwind scheme)

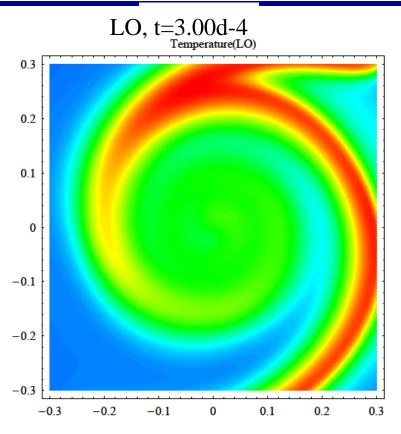
CPU factor: 15.3

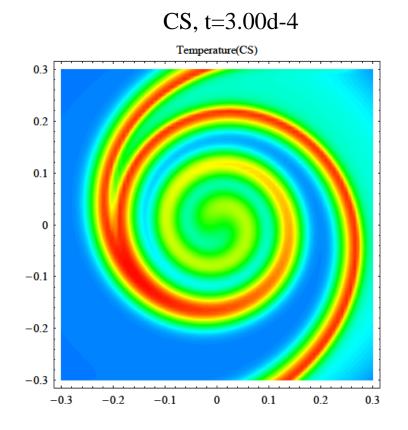




### Flame Roll Up in a Vortex – Re = 600 Conventional vs. implicit-compact method







### **Spatial discretization**

• Grid: quasi-uniform,  $\Delta x \approx 0.008$ 

Order: 1<sup>st</sup> (upwind scheme)

CPU factor: 1

### **Spatial discretization**

• Grid: quasi-uniform,  $\Delta x \approx 0.008$ 

Order: 4<sup>th</sup> – 6<sup>th</sup> (compact scheme)

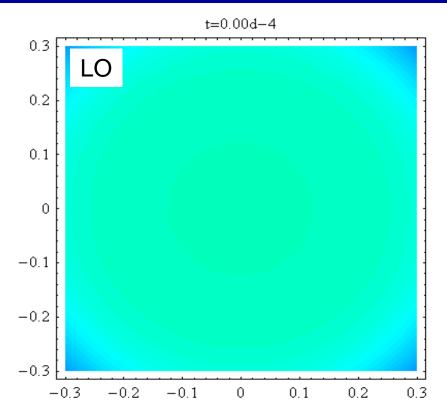
• CPU factor: 1.2

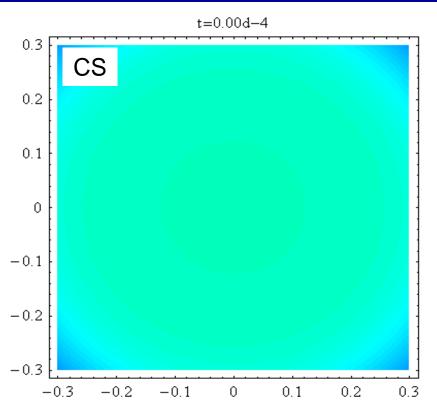




## Flame Roll Up in a Vortex – Re = 600







### **Spatial discretization**

- Grid: quasi-uniform,  $\Delta x \approx 0.008$
- Order: 1<sup>st</sup> (upwind scheme)
- CPU factor: 1

### **Spatial discretization**

- Grid: quasi-uniform,  $\Delta x \approx 0.008$
- Order: 4<sup>th</sup> 6<sup>th</sup> (compact scheme)
- CPU factor: 1.2





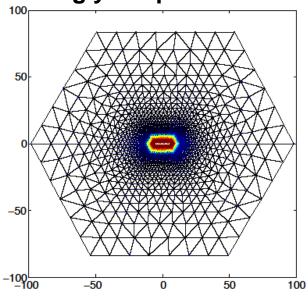
# Multiscale Modeling and Computation for Materials

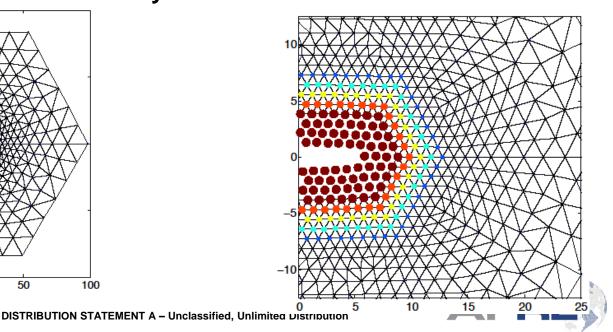


- New research thrust New core projects, a MURI 2012 in Managing Data Complexity in Predictive Material Science, and a COE on Integrated Computational Material Science and Engineering (ICMSE), 2013 MURI on Peridynamics
- "The underlying physical laws necessary for the mathematical theory of a large part of physics and the whole of chemistry are thus completely known, and the difficulty is only that the exact application of these laws leads to equations that are much too complicated to be soluble."
   P. A.M. Dirac, Proc. Royal Soc. 123 (1929), 714-733
- Dirac's quote true today, and relevant. Most new technologies of interest to the Air Force can be analyzed by equations known (in 1929) to be accurate and predictive, but we are unable to do it: The discipline that is needed most: Computational Mathematics
- Approach:
- 1) By evaluating all competing multiscale methods on the basis of rigorous error analysis and systematic numerical testing
- 2) New multiscale approaches for design of new materials Objective Structures

# Multi-scale Materials Computing Mitch Luskin (Univ of Minnesota)

- Multiscale computational methods for materials need to be validated by benchmark numerical experiments designed and evaluated on the basis of theoretical error analysis.
- Theory-based benchmarking for material failure
- Crystal defects such as grain boundaries, cracks, and dislocations play a central role in determining material behavior for Air Force applications.
   The key difficulty in simulation is that crystal defects affect elastic fields far beyond their immediate atomistic neighborhood and give rise to strongly coupled multi-scale systems.



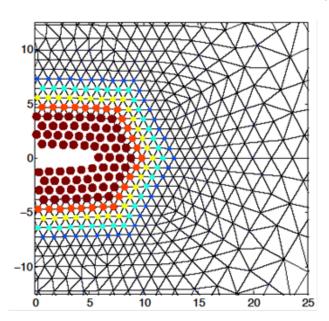


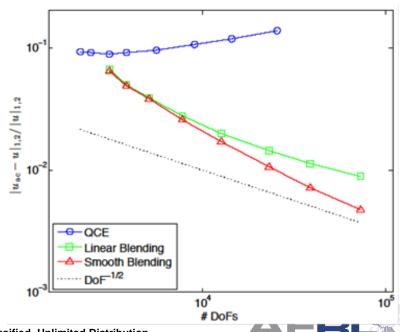


# Computational Complexity of Defects



- Identify the quantity of interest (material failure, strength, toughness, etc.) and utilize multiscale error analysis to determine the complexity (number of degrees of freedom) to compute the quantity of interest to the required tolerance.
- The Blended Quasicontinuum Energy is the first atomistic-to-continuum energy for many-body interactions and multi-lattices with a controllable error. Numerical results for a microcrack are exactly predicted by theoretical complexity estimates.





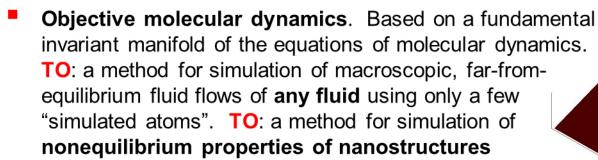


### Multiscale Methods for Materials,

Kaushik Dayal (CMU) & Richard D. James (UMN)

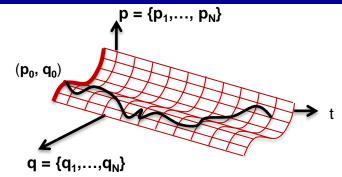


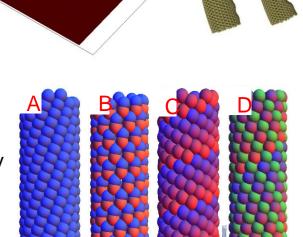
- Approach: use the underlying invariance\* of quantum mechanics as the main principle for simplification
  - \* Frame-indifference and permutation invariance
- Some current implementations of this idea



 Objective DFT: An advanced DFT method for nonperiodic nanostructures. TO: predict collective properties (ferromagnetism, ferroelectricity, flexoelectricity, etc.) of nanostructures from first principles

Objective self-assembly: TO: predictive design of functional macromolecules to enable tailored self-assembly of nanostructures







## Uncertainty Quantification Efforts – MURI '09 and Core Projects



- ➤ Uncertainty Quantification (UQ): The process of quantifying uncertainties associated with model calculations of true, physical Quantities of interest (QOIs) with the goal of accounting for all sources of uncertainties and quantifying the contributions of specific resources to the overall uncertainty. From "Assessing the Reliability of Complex Models" NRC report in 2012
- ➤ MURI Effort: To develop rigorous theory, algorithms and software for UQ management in a computationally scalable way. A unique effort in terms of its breadth of topics and approaches, and its impact on the field.
- ➤ 5 Research Thrusts:
  - Mathematical Analysis and Multiscale Formulation of SPDEs
  - Numerical Solution of SPDEs
  - ➤ Reduced-Order Modeling
  - **➤ Design & Control Under Uncertainty\***
  - **➤ Multiscale Property Estimation\*\***











### **Research Highlights**



- ➤ Mathematical Theory: Quantization-renormalization of SPDEs; New evolution equations for joint-pdf of SPDEs; Nonlinear Malliavin calculus
   ➤ Reduced Basis Methods (RBM): Integral equations and multi-scattering problems; Robust design, parameter estimation, and model uncertainty
- Adaptive ANOVA: Convergence theory; Parameter compression and RBM; Fluid flows, porous media, multi-scattering
- ➤ Bayesian Framework: Coarse-graining; Active learning + SPDEs; Adaptive SMC, dependent random variables, Model uncertainty in inverse problems
- **▶ Design Under Uncertainty: Multi-Fidelity approaches**
- Numerical SPDEs: Data-driven stochastic multiscale method, Multiscale multilevel MC, Probabilistic graphical models, Long-time integrators of SPDEs
- ➤ Software: MEPCM library; Reduced basis method libraries RBOOMIT, RBAppMIT; Akselos, Inc; Random poly-crystals RPCrystal



### **Design Under Uncertainty**

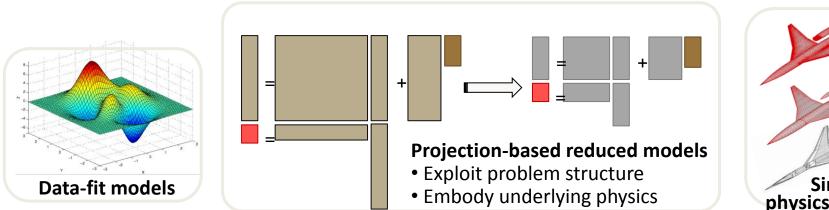
P Huynh, C Lieberman, L Ng, K Willcox (PI)



**Multifidelity approaches**: How should we best use all available models and data in concert to achieve:

Better decision-making (optimization, control, design, policy)

Better understanding of modeling limitations





**Research objectives**: Develop and apply new multifidelity methods for design under uncertainty

Multifidelity model construction (certified reduced basis models)

Quantification of uncertainty and model fidelity (how good is a model for a given purpose)

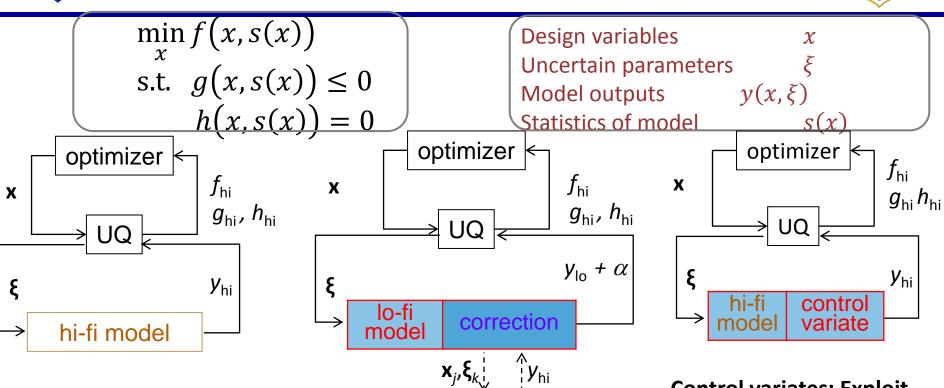
Multifidelity model management (which model to use when, convergence guarantees, model adaptation, model-data fusion)



### Multifidelity Optimization under Uncertainty







#### **Traditional OUU methods**

 Require thousands of highfidelity model evaluations at each optimization iteration

### Adaptive corrections: Exploit model local accuracy

hi-fi model

 Computed using occasional recourse to highfidelity model

### Control variates: Exploit correlation between highand low-fidelity models

 Reduce high-fidelity samples needed at optimization iterations

Surrogates constructed to have desirable properties (e.g., for convergence)



## Multifidelity methods lead to large computational savings, making optimization under uncertainty tractable



Design under uncertainty of an acoustic horn.

Decision variables: horn geometry, b

**Uncertainty**: wavenumber, wall impedances

Output of interest: reflection coefficient,  $s_r$ 

$$\min_{b} \mathbb{E}[s_r] + \sqrt{\mathbb{V}\mathrm{ar}[s_r]}$$



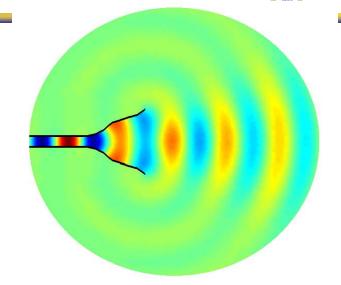
Finite element model (35,895 states)

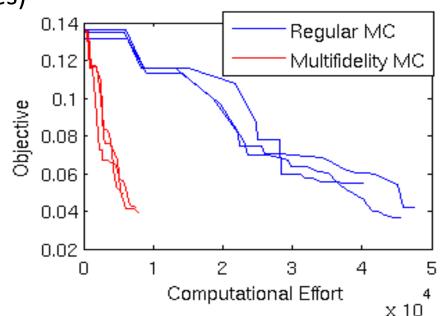
Reduced basis model (30 states)

### Multifidelity approach:

Control variates

	Equivalent number of hi-fi evaluations		
Regular Monte Carlo	44,343		
Multifidelity Monte Carlo	6,979	(-84%)	



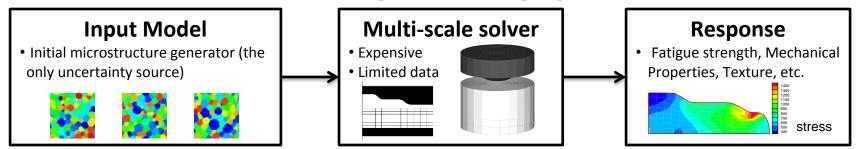




## Uncertainty propagation using probabilistic graphical models



### Application: Multiscale aircraft engine disk forging problem



### **Probabilistic Graphical model framework**

#### Structure design

 Decompose the joint distribution on a graph using localized potentials

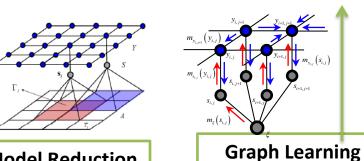
#### Inference

· Infer the marginal distribution of the response (calculate the statistics)

Learning all the

the graph (EM)

unknown parameters in



#### **Model Reduction**

 Localized model reduction scheme

### **Surrogate model**

**Example: Strength** 

MC (N = 4800)

New Observation of the input

Mean

std

**Localized Input** Model Reduction

#### Inference

Infer the conditional distribution



**Graphical Model** 

(N = 500)



# Ultra-Scalable Algorithms for Large-Scale Uncertainty Quantification in Inverse Wave Propagation



G. Biros, T. Bui-Thanh, L. Demkowicz, O. Ghattas, J. T. Oden, G. Stadler (UT-Austin)

- Problem: Address inverse problem (aka calibration or parameter estimation) in the framework of Bayesian inference: given a model with uncertain parameters and noisy observations of model outputs, estimate the model parameters and quantify uncertainties in the estimate
- Current state-of-the-art Markov chain Monte Carlo (MCMC) methods are prohibitive
- The issue with current MCMC methods: their inability to exploit problem structure
- The overarching goal is to overcome the "curse of dimensionality" by exploiting the structure of the posterior probability density function (pdf)
  - Insight: Hessian operator of the parameter-to-observable map defines local correlation structure of posterior pdf, and can be used to accelerate MCMC sampling
  - Construct adjoint-based low-rank approximation of Hessian to make tractable
  - Develop theory at infinite dimensional level, ensure mesh-independence of finite dimensional discretization
  - Develop parallel implementations that scale to the limits of modern supercomputers

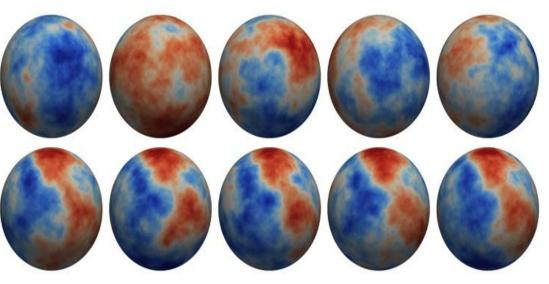




# Transformational Opportunities



- Tailor theory to structure of inverse wave propagation problems
  - Estimate heterogeneous material properties from scattered waves
- Preliminary results demonstrate 1000X speedups on small problems relative to conventional MCMC methods; permit solution of large problems that were previously intractable
- Million-parameter example from acoustic wave propagation: infer global heterogeneous wave speed from surface observations of seismic waveforms
  - 1.07 million uncertain parameters
  - 630M states, 2400 time steps
  - Observations only in N Hemisphere
  - 100K cores on Jaguar Cray XK6
  - 2000X effective dimension reduction
  - Top row: samples from the prior
  - Bottom row: samples from posterior
  - Differences between rows indicate knowledge gained from data





### **Summary**



- Continued support of high-order methods in multiscale and multiphysics modeling, support in time-integration methods
- Continued emphasis on UQ and V&V
  - New approached for reducing the curse of dimensionality (PDF methods), Optimal Statistical Estimators, Sampling methods, Design under Uncertainty
- Algorithms for multi-core platforms: GPU computing
- Emphasis on scalability of algorithms for ultra-parallel large scale computing
- Understanding the impact of geometric discretization on the fidelity of the analysis and computation

